Polynomial Regression

Contents

Introduction	1
Simulating data	1
Fitting the Data	2

Introduction

Polynomial regression is a tool that allows us to understand and predict the behavior of complex data. Unlike linear regression, which assumes a linear relationship between the independent and dependent variables, polynomial regression can model nonlinear relationships by incorporating polynomial terms.

First, we consider a univariate model:

$$y_i = f(x_i) + \varepsilon_i, \quad i = 1, \dots, n, \tag{1}$$

In polynomial regression, f is a polynomial function of degree q, expressed as:

$$f(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \dots + \beta_q x^q$$

where β_j are the coefficients for $j=0,\ldots,q$. The model then can be represented as:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_q x_i^q + \varepsilon_i, \quad i = 1, \dots, n.$$

The coefficients β are estimated using linear regression, considering the model $y = X\beta + \varepsilon$, where $X = [1, x, x^2, \dots, x^q]$ and $\beta = [\beta_0, \beta_1, \beta_2, \dots \beta_q]^T$.

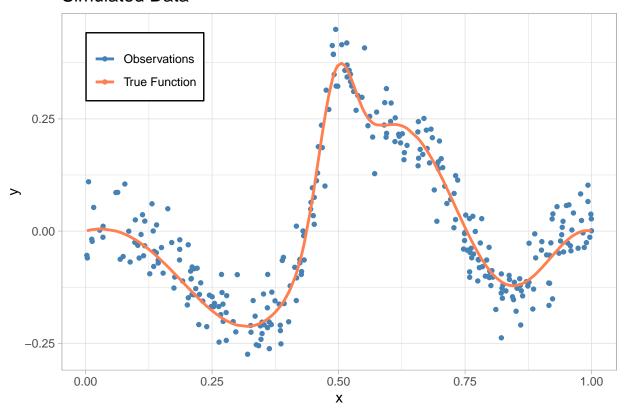
Simulating data

For our examples, we will simulate data to explore how well polynomial regression can fit oscillating values.

To visualize the data, we utilize ggplot2:

library(ggplot2)

Simulated Data



ggsave("graphs/PolynomialRegression.pdf", width = 10, height = 6, dpi = 300)

Fitting the Data

We fit the data using the 1m function from the stats package, starting with a polynomial of degree 8.

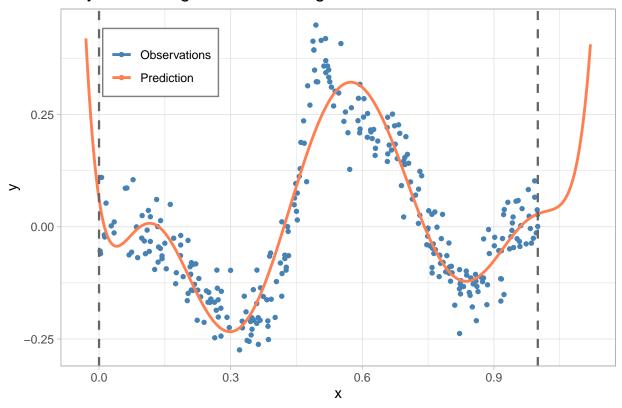
```
polynomial <- lm(y.obs ~ poly(x, degree=8, raw=TRUE))
x.pred <- seq(-0.03, 1.12, length.out = 300)</pre>
```

```
y.pred <- predict(polynomial, newdata = data.frame(x = x.pred))</pre>
```

The results are displayed as follows:

```
data.polynomial <- data.frame(x, y.obs, x.pred, y.pred)</pre>
ggplot(data = data.polynomial) +
  geom_point(aes(x = x, y = y.obs, color = "Observations"),
             shape = 20, size = 2) +
  geom_path(aes(x = x.pred, y = y.pred, color = "Prediction"), linewidth = 1) +
  geom_vline(xintercept = 0, linetype = "dashed", color = "gray40",
             linewidth = 0.8) +
  geom vline(xintercept = 1, linetype = "dashed", color = "gray40",
             linewidth = 0.8) +
  scale color manual(values = c("Observations" = "steelblue",
                                "Prediction" = "coral")) +
  labs(title = "Polynomial Regression with degree 8",
       x = "x"
       y = "y"
       color = NULL) +
  theme_light() +
  theme(plot.title = element_text(size = 14),
        legend.position = c(0.18, 0.85),
        legend.background = element_rect(fill = "white", colour = "gray50"))
```

Polynomial Regression with degree 8



ggsave("graphs/PolynomialRegression1.pdf", width = 10, height = 6, dpi = 300)

In this graph, we observe that the high degree allows the model to accurately fit the data within the variable

X range (in this case, [0,1]). However, outside this range, the model predictions increase rapidly, which illustrates the potential risks of using high-degree polynomials without appropriate constraints. Now, we will explore the effects of using different polynomial degrees:

```
poly.3 <- lm(y.obs ~ poly(x, degree=3, raw=TRUE))
poly.5 <- lm(y.obs ~ poly(x, degree=5, raw=TRUE))
poly.10 <- lm(y.obs ~ poly(x, degree=10, raw=TRUE))
poly.20 <- lm(y.obs ~ poly(x, degree=20, raw=TRUE))</pre>
```

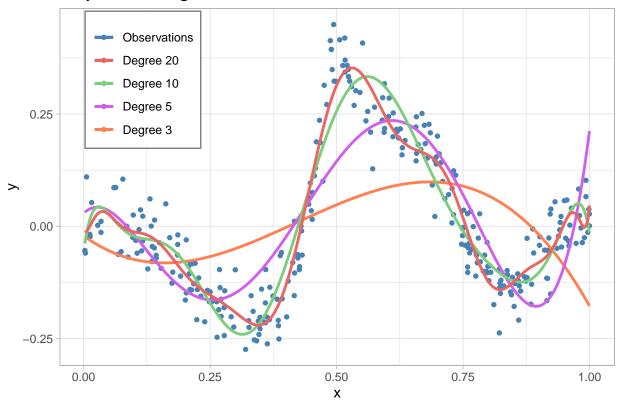
We can examine the coefficients and other statistical details by using:

```
summary(poly.3)
```

```
##
## Call:
## lm(formula = y.obs ~ poly(x, degree = 3, raw = TRUE))
##
## Residuals:
       Min
                  1Q
                       Median
                                     3Q
                                             Max
## -0.29222 -0.12579 -0.00821 0.10024 0.40436
##
## Coefficients:
##
                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                                                 0.03963 -0.534 0.59378
                                     -0.02116
## poly(x, degree = 3, raw = TRUE)1 -0.82190
                                                 0.31472 -2.612 0.00947 **
## poly(x, degree = 3, raw = TRUE)2 3.17293
                                                 0.69780
                                                          4.547 7.94e-06 ***
## poly(x, degree = 3, raw = TRUE)3 -2.50773
                                                 0.44678 -5.613 4.58e-08 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1469 on 296 degrees of freedom
## Multiple R-squared: 0.1958, Adjusted R-squared: 0.1877
## F-statistic: 24.03 on 3 and 296 DF, p-value: 6.059e-14
Next, we make predictions using these models:
x.pred \leftarrow seq(min(x), max(x), length.out = 300)
y.pred3 <- predict(poly.3, newdata = data.frame(x = x.pred))</pre>
y.pred5 <- predict(poly.5, newdata = data.frame(x = x.pred))</pre>
y.pred10 <- predict(poly.10, newdata = data.frame(x = x.pred))</pre>
y.pred20 <- predict(poly.20, newdata = data.frame(x = x.pred))</pre>
```

The visualizations of these predictions are as follows:

Polynomial Regression



ggsave("graphs/PolynomialRegression2.pdf", width = 10, height = 6, dpi = 300)